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The goal of the "Chihuahua vs. Muffin" workshop was to give participants practical experience with transfer learning and convolutional neural networks for image classification. The main goal was to create a model that could tell the difference between pictures of muffins and chihuahuas. Preprocessing the data, training the model with PyTorch, and assessing the model's performance were among the methods employed. Important ideas like data augmentation, normalization, and the application of pre-trained models to improve learning efficiency were also covered in the workshop.

The basic task of image classification in computer vision is to identify a label from a predefined set of categories for an input image. In order to do this, a machine learning model must be trained to identify patterns and features in pictures that belong to various classes. For instance, the model learns to discriminate between pictures of muffins and chihuahuas in the "Chihuahua vs. Muffin" workshop.

A particular kind of deep learning model called Convolutional Neural Networks is made especially for handling structured grid data, such as images. They consist of multiple essential layers. Convolutional layers use kernels to apply convolution operations to the input image and extract features like textures, shapes, and edges. As the filters pass over the image, feature maps are produced that draw attention to the locations of particular features. By reducing the spatial dimensions of the feature maps, pooling layers help to manage overfitting and lower the computational load. Average and maximum pooling are two popular forms of pooling. The network gains non-linearity from activation functions, which enables it to learn increasingly intricate patterns. CNNs frequently use the Rectified Linear Unit function. Completely Interconnected Layers Usually located at the end of the network, these layers are responsible for combining the features that the convolutional layers extracted to create the final classification.

Using a pre-trained model on a novel but related task is known as transfer learning. With this method, performance on a smaller, task-specific dataset is enhanced by utilizing the knowledge gathered from a larger dataset. Transfer learning can be used in the workshop to refine a CNN that has already been trained on the chihuahua vs. muffin classification task, which can drastically cut down on training time and increase accuracy.

Handling the code's attribute and syntax mistakes presented a big challenge. For example, I ran into a syntax error because of a placeholder in the code, but it was fixed when I instantiated the neural network model correctly. Making sure data loaders were configured correctly, which necessitated defining suitable batch sizes and transformations, presented another difficulty. I was able to troubleshoot and find solutions for these problems by carefully reading error messages and consulting documentation also using the google.

I now have a better understanding of how CNNs can be applied to image classification tasks thanks to this workshop. I gained knowledge about the significance of normalization and data preprocessing in enhancing model performance. I also understood how important transfer learning is for cutting down on training time and increasing accuracy by using pre-trained models. This workshop also emphasized how model development is iterative, and that constant testing and improvement are necessary to get the best results.

Classifying medical images to aid in diagnosis is one of the many real-world applications of the techniques learned in this workshop. Autonomous Vehicles is Identifying objects and obstacles in the environment. Surveillance and facial recognition systems are being improved by security systems. Retail is using image recognition to improve inventory management and product classification. These are extremely valuable skills in the field of computer vision and machine learning, as they form the basis of many advanced applications.

I learned a lot from this workshop and now have a better understanding of image classification and machine learning. The practical approach gave students real-world experience using PyTorch for deep learning tasks and helped cement theoretical concepts. Getting past the obstacles we faced in the workshop increased my confidence in debugging and troubleshooting code. All in all, this experience has inspired me to learn more about machine learning and its potential uses.

**References:**

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